Texture Based Steganalysis of Grayscale Images Using Neural Network

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Abstract

A method of steganalysis of grayscale images based on texture analysis using Spatial Gray Level Dependence Method is presented. A neural network trained with the texture related statistics, extracted from cover images and stego images that are created using one embedding algorithm, is adopted as a classifier. The classifier reliably detects clean images and stego images despite the small data embedding rate of 0.0077. Steganographic tools tested include both spatial and transform domain image hiding techniques. It is worth mentioning that the clean images are effectively distinguished from the stego images on the basis of image texture alone, regardless of the embedding algorithm used.

Keywords

Steganography; Steganalysis; Texture Analysis; SGLDM; Spatial Gray Level Dependence Method; Neural Network

Introduction

Steganalysis is the art and science of detecting the presence of hidden information in digital media embedded using steganography (*N. F. Johnson, 1998; J. Fridrich et al., 2001; J. Fridrich, 2002*). A number of steganalysis techniques have been put forward in the literature. Classification of these techniques is given in (*Arooj, 2010*). Some of the techniques given in (*N. F. Johnson, 1998; M. Niimi et al., 2001; J. Fridrich et al., 2001; Tariq Al Hawi et al., 2004*) exploit the signatures introduced by certain steganographic algorithms while as the techniques given in (*I. Avcibas et al., 2001; I. Avcibas et al., 2002; J.J. Harmsen, 2003; R. Chandramouli, 2003; J. Fridrich et al., 2003; S. Dumitrescu et al., 2003; K. Sullivan et al., 2004; K. Sullivan et al., 2005; Xiang-dong Chen et al., 2006*) identify characteristic side effects in statistics caused due to embedding algorithm and exploit the same for steganalysis. The above techniques prove useful only if the steganographic algorithm used is known. The other set of techniques given in (*S. Lyu, 2002; S. Lyu, 2004; Wen-Nung Lie, 2005; G. Xuan et al., 2005; Yun Q. Shi et al., 2005; Xiaochuan Chen et al., 2006; Patricia Lafferty, 2004*) find out some appropriate statistics that are changed due to any steganographic algorithm and hence do not depend on the behavior of embedding algorithm. Such techniques can be fruitful in a practical scenario of steganalysis wherein there is neither any scope of comparison with the original images nor the embedding algorithm is known apriori. Because of nature of field, the steganographic algorithms are constantly enhanced rendering the proposed steganalytic techniques useless. Hence with the ever increasing number of steganographic techniques, it will be reasonable to devise a steganalytic technique that can detect the presence of secret information embedded using any steganographic algorithm.

Work has been carried out for steganalysis of images based on texture analysis and is reported in (*Patricia Lafferty, 2004; Shaohui Liu et al., 2004*). The technique for steganalysis of images given in (*Shaohui Liu et al., 2004*) analyses texture in wavelet domain and the technique proposed in (*Patricia Lafferty, 2004*) analyses texture in spatial domain by deriving first order statistics (statistical texture analysis). Literature survey (*Arooj, 2010*) reveals that second order texture statistics has not been analysed for the purpose of steganalysis. In this paper, we propose a new steganalysis technique based on statistical texture analysis in spatial domain deriving second order statistics using Spatial Gray Level Dependence Method (SGLDM) (*R. M. Harlick et al., 1973*). The rest of the paper is organized as follows: section 2 deals with texture analysis of images. In section 3, neural network is trained with the features

obtained from section 2. Section 4 and 5 give the implementation and experimental results. Discussion and conclusion is presented in section 6.

Texture Analysis Using SGLDM

Steganography essentially alters the cover image to embed the secret data though the presence of secret data is imperceptible to eyes. So for steganalysis of images we propose to analyze the imperceptible texture by deriving the second-order statistics using SGLDM. The spatial grey level dependence aspect of texture is concerned with the spatial distribution and spatial dependence among the grey levels in a local area. Being one of the most successful methods for texture discrimination at present (*A. H. Mir et al., 1995*), we have investigated its effectiveness for steganalysis of images. This method is based on the estimation of the second order joint conditional probability density function, $f(i,j|d,\theta)$: where θ = 0, 45, 90, 135, 180, 225, 270, and 315 degrees. Each $f(i,j|d,\theta)$ is the probability of going from gray level i to gray level j, given that the inter-sample spacing is d and the direction is given by the angle θ. The estimated value for these probability density functions can thus be written in matrix form:

$$\phi(d,\theta)=[f(i,j|d,\theta)] \quad \text{........(1)}$$

For computing these probability distribution functions, scanning of the image in four directions viz., θ = 0, 45, 90, and 135 degrees is sufficient, since the probability density matrix for the rest of the directions can be computed from these four basic directions.

Let $\phi^t(d,\theta)$ denote the transpose of the matrix $\phi(d,\theta)$ for the intersample spacing, d, and direction, θ.

$$\phi(d,0) = \phi^t(d, 180)$$

$$\phi(d,45) = \phi^t(d,225)$$

$$\phi(d,90) = \phi^t(d,270)$$

$$\phi(d,135) = \phi^t(d,315)$$

Thus, the knowledge of $\phi(d,180)$, $\phi(d,225)$, $\phi(d,270)$, $\phi(d,315)$ add nothing to the characterization of texture. If one chooses to ignore the distinction between opposite directions, then symmetric probability matrices can be employed. If this condition is acceptable, then the Spatial Grey Level Dependence Matrices or Gray Level Co-occurrence Matrices (GLCM) $S_0(d)$, $S_{45}(d)$, $S_{90}(d)$, and $S_{135}(d)$ can be found from

$$S_0(d) = \tfrac{1}{2}[\phi(d,0) + \phi(d,180)]$$

$$= \tfrac{1}{2}[\phi(d,0) + \phi^t(d,0)]$$

In general,

$$S_\theta(d) = \tfrac{1}{2}[\phi(d,\theta) + \phi^t(d,\theta)] \quad \text{.......(2)}$$

Features

Using this method, approximately two dozen co-occurrence features can be obtained (*R. M. Harlick, 1978*). In this study, the representation is restricted to five features only, which we hypothesize will provide useful information for pattern recognition:

1)E:Energy $$E(S_\theta(d)) = \sum_{i=0}^{NG-1}\sum_{j=0}^{NG-1}[\ S_\theta(i,j)\,|\,d\ ]^2 \quad \text{........(3)}$$

2)H:Entropy

$$H(S_\theta(d)) = \sum_{i=0}^{NG-1}\sum_{j=0}^{NG-1} S_\theta(i,j\,|\,d)\log S_\theta(i,j\,|\,d) \quad \text{........(4)}$$

3)L:Local homogeneity

$$L(S_\theta(d)) = \sum_{i=0}^{NG-1}\sum_{j=0}^{NG-1}(1/(1+(i-j)^2))S_\theta(i,j\,|\,d) \quad \text{........(5)}$$

4)C:Contrast

$$C(S_\theta(d)) = \sum_{i=0}^{NG-1}\sum_{j=0}^{NG-1}(i-j)^2 S_\theta(i,j\,|\,d) \quad \text{.......(6)}$$

5)Cr:Correlation

$$C_r{}^{/}(S_\theta(d)) = \sum_{i=0}^{NG-1}\sum_{j=0}^{NG-1}((i-\mu_i)(j-\mu_j)S_\theta(i,j|d))/\sigma_i\sigma_j \quad \text{.........(7)}$$

Where $S(i,j|d)$ is the (i,j)th element of S(d) and NG is the number of grey levels in the picture from which spatial grey level dependence matrices are obtained and μ and σ are mean and standard deviation respectively.

Neural Network as a Classifier

In our work, a multilayer feed-forward neural network with back-propagation (BP) training

algorithm is used as the classifier. BP networks have been found to be useful in addressing problems requiring recognition of complex patterns and performing non-trivial mapping functions (*J. A. Freeman, 2005*). In many pattern recognition tasks, gradient descent techniques, used in BPN, are practical and robust (*J. A. Anderson, 2004*). The structure of neural network used consists of an input layer, four tan-sigmoid neuron hidden layers and one linear neuron output layer. From the experimental results it has been concluded that the linear output neuron provides a higher classification rate than the non-linear outputs. This neural network is trained with the texture related features obtained from implementation of equations3 to equation 7 given in section2.

Implementation

The construction of an image database is fundamental and important in steganalysis research. Using Bigfoto image database (http://www.bigfoto.com/), we have downloaded 902 JPEG sample colour images of same size with quality factors ranging from 70 to 90. These downloaded images are pictures of nature, ocean, food, animals, architecture, places, people etc. Since these images are uploaded by user there is a possibility that some of the images are stego. However, this will not create any problem for testing our methodology as our objective is to capture changes in imperceptible texture before and after we embed data in them. In addition to these downloaded images, our database contains four sets of stego images generated randomly from the sample cover images using four steganography algorithms, viz., S-tools4 (http://www.stegoarchive.com/), JPHS05 (http://www.stegoarchive.com/), STEGHIDE (http://www.stegoarchive.com/) and F5 (http://wwwrn.inf.tu-dresden.de/). The input cover image format used in JPHS05, STEGHIDE and F5 is JPEG file whereas in S-tools BMP file, converted from downloaded JPEG, is used. While multitudes of data can be hidden in an image, however to ensure imperceptibility it is recommended that the embedded bit rate is less than 0.02 bpp (*Patricia Lafferty, 2004*). To make our results persuasive, we hide a very small amount of data, 56 bytes, in these images keeping the embedded bit rate only 0.0077 bpp.

To check efficacy of texture analysis, we propose the use of Spatial Gray Level Dependence Method of texture analysis for steganalysis. The texture analysis implementation is based on the Image Processing Toolbox of MATLAB 7.3. For texture analysis the colour images (cover and stego) are first converted to the grayscale images as SGLDM is applicable to grayscale images only. MATLAB converts the RGB values to NTSC coordinates, sets the hue and saturation components to zero, and then converts back to RGB color space. Using SGLDM we have extracted five texture related statistical features (contrast, homogeneity, energy, correlation and entropy) of an image before and after embedding, i.e., texture analysis of sample cover image and its stego version. The total number of Gray Level Co-occurrence Matrices (GLCMs) is 32 as 'd' is set to 8 and θ = 0, 45, 90, 135 degrees (section 2). Hence each feature extracted from an image has a length of 32. The outputs of the texture analysis form the inputs to the neural network. Since from each image 5 feature vectors are extracted, each of length 32, a 160-D feature vector is produced from each image. Hence 160-D feature vectors are used as the inputs to the neural net for each test image. The experimental results show that increasing inter-sample spacing 'd' beyond 8 does not improve the steganalysis performance but only leads to computational complexity in NN.

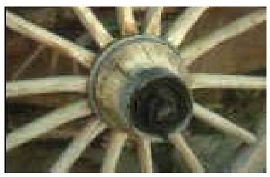
The neural network is trained with proposed texture related statistics of 902 clean original images and their corresponding 902 stego images modified using F5 (total 1804 images). To evaluate the performance of the neural net, it is simulated and tested for the clean images and the stego-images created using four different data hiding methods. The neural network implementation is based on the Neural Network Toolbox of MATLAB 7.3.

Experimental Results

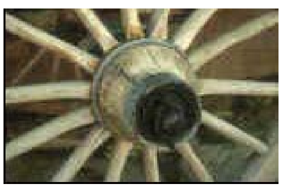
We show the plots of proposed texture features to illustrate the effectiveness of the selected features. The grayscale images obtained from a randomly selected original clean colour image and its four stego versions are shown in Fig.2.

1 (A): ORIGINAL IMAGE

1 (B): STEGO-IMAGE (F5)



1(C):STEGO-IMAGE (JPHS05)



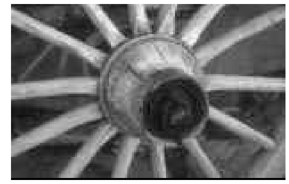
1(D): STEGO-IMAGE (STEGHIDE)

1(E): STEGO-IMAGE(S-TOOLS)

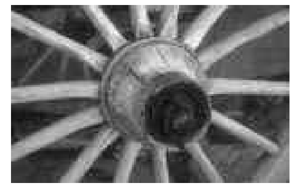
FIGURE 1: ORIGINAL AND STEGO COLOUR IMAGES

2 (A): ORIGINAL IMAGE

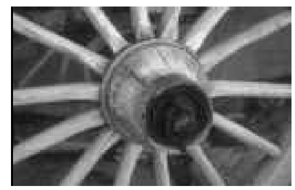
2 (B): STEGO-IMAGE (F5)



2(C):STEGO-IMAGE (JPHS05)



1(D): STEGO-IMAGE (STEGHIDE)



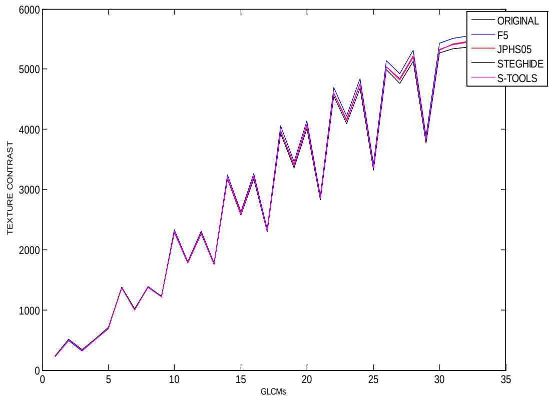
1 (E):STEGO-IMAGE (S-TOOLS)

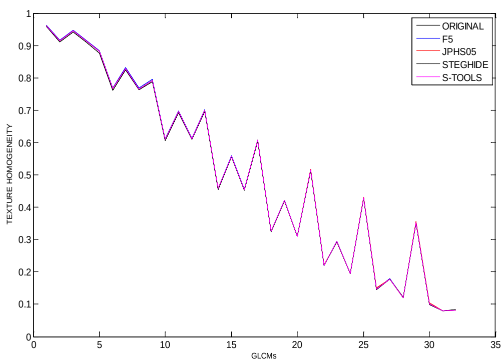
FIGURE 2: ORIGINAL AND STEGO GRAYSCALE IMAGES

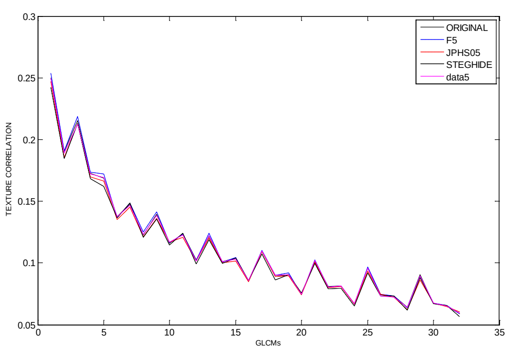
Plots of proposed five texture features against Grey Level Co-occurrence Matrices (GLCM) for different values of 'd' and 'θ' for this clean image and its four stego versions are shown in Fig.3. The zoom in of Fig.3 is shown in Fig.4. Due to space limit, these figures are displayed in small size. However, readers are recommended to view these figures clearly by using zoom to 500%. For all the four stego images, comparison of a texture feature for each GLCM w.r.t the original image shows a significant difference. However, mostly the variation is different for different embedding tools; though the followed pattern is somewhat similar.

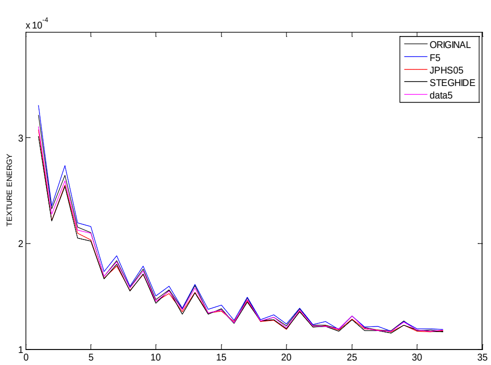
Whereas it is evident, that texture parameters are able to discriminate between a clean image and its any stego version the main issue, however, is to build a system that can be used to determine if a particular image is clean or stego. For this, we have used a BP neural network as a classifier. The neural net is trained, simulated and tested as discussed in section 4. The detection rates of various embedding algorithms are given in Table1. It should be noted that the proposed technique of steganalysis is universal or blind as it can detect stego-images irrespective of the nature of the steganographic algorithm used for embedding.

Comparison of detection rates with some of the methods whose data embedding rates were available in the literature is given in Table 2.









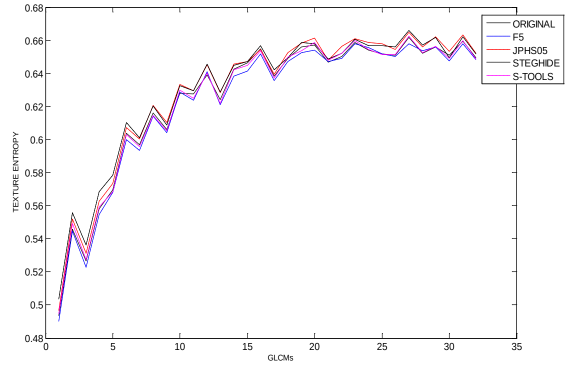
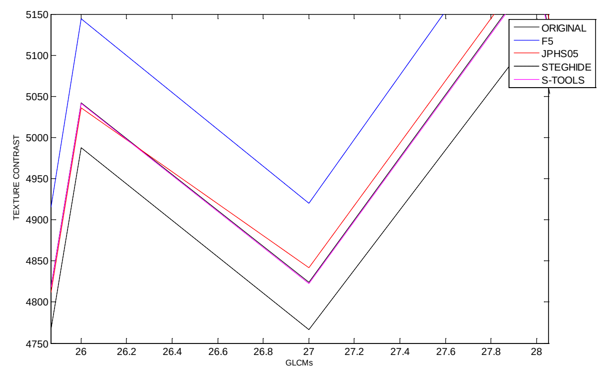
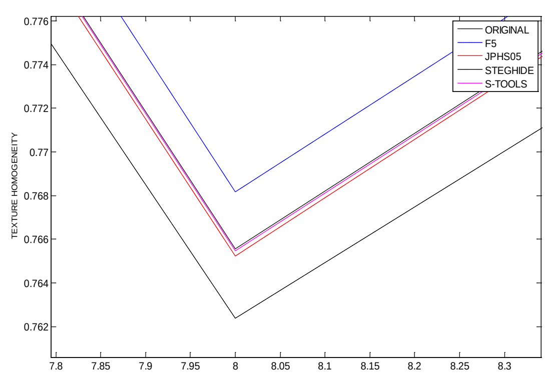
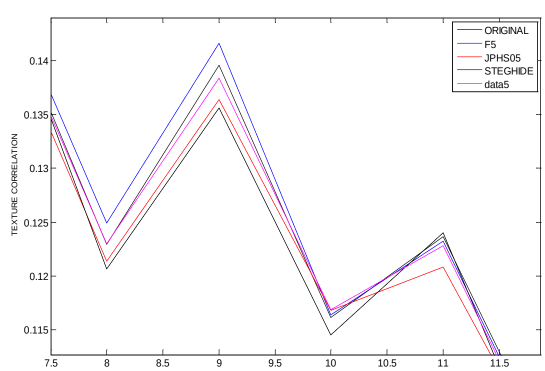


FIGURE 3: PLOTS OF PROPOSED FIVE TEXTURE FEATURES AGAINST GLCM FOR DIFFERENT VALUES OF d AND θ.







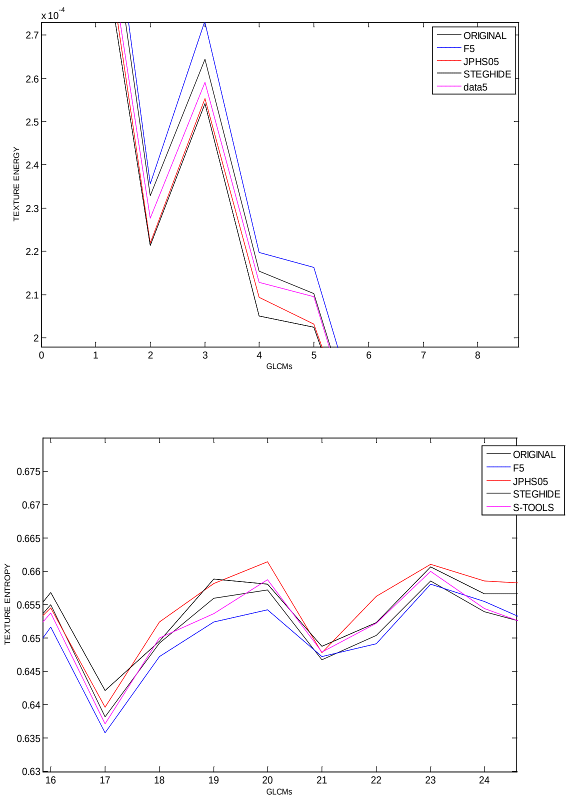


FIGURE 4: ZOOM IN OF FIG.3

TABLE 1: STEGANALYSIS RESULTS OF PROPOSED TECHNIQUE

Image Set	Correct Detection	Detection Rate
Clean images	841/902	93.23%
F5	828/902	91.79%
S-TOOLS	155/187	82.88%
JPHS05	158/200	79%
STEGHIDE	193/255	75.68%

TABLE 2: COMPARISON OF PROPOSED TECHNIQUE WITH OTHER METHODS

Embedding Algorithm	Embedded Rate (bpp)	Method	Detection Rate
Generic LSB	0.3	Yun Q. shi	98.9%
	0.3	Farid	71.9%
	0.3	Harmsen	56.5%
	0.01	Avcibus	85%
	0.01	Avcibus	75%
	0.1	Xiang-dong	59.23%
	0.0077	proposed	82.88%
F5	0.01	Avcibus	80%
	0.01	Xiang-dong	43.08%
	0.0082	Patricia	86.5%
	0.0077	Proposed	91.79%

Discussion and Conclusion

In the last decade many steganalytic techniques for images have been proposed in the literature. In this work an attempt has been made to examine the usefulness of spatial domain statistical texture analysis technique, SGLDM, for the purpose of steganalysis. Four steganographic algorithms were used to embed the data. The images were embedded with an embedded rate of 0.0077 bpp; a rate very low from steganalysis point of view. The embedding of the data was done in spatial as well as in transform domain. The results of texture analysis of clean and its stego versions have shown significant change in the texture parameters with respect to each GLCM (d=1,2..,8 and theta is 0,45,90,135 degrees). And making d > 8 only leads to computational complexity without any improvement in results. The potential of using 2nd order texture statistics derived from SGLDM has been demonstrated for the purpose of steganalysis. It is worth mentioning that texture features (w.r.t GLCMs) of stego images follow the pattern of texture features of clean images irrespective of the embedding domain though the inter-difference of the parameters of stego images with respect to clean images is different for different embedding tools. An important conclusion that can be drawn is that the variations of texture features of stego images from a clean image are independent of inter-sample space 'd'. This also supports our assertion that increasing d>8 only increases computational complexity at no advantage. Usefulness of these parameters in steganalysis especially for transform domain embedding is a noteworthy advantage; since embedding in transform domain is not generally susceptible to common cover attack (*Der- Chyuaun Lou, 2002*).

One of the important points to notice is that discrimination of stego images from clean images has been done despite the fact that embedding has been done to colour images and that the grayscale images, obtained from colour images, are used for testing.

To classify the images into classes: Clean and Stego, a classification technique based on Back Propagation Model of NN has been used. A data base of 1804 images has been used to train the net. The recognition rate as given in Table 1 has been obtained.

It is obvious that detection rate will be improved if embedded rate is increased. The recognition rate can be further improved if the larger image data base is used for training the NN. It is clear from Table 2 that the proposed technique performs better than other specified techniques.

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